Soil Electrical Conductivity and Topography Related to Yield for Three Contrasting Soil–Crop Systems

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ABSTRACT

Many producers who map yield want to know how soil and landscape information can be used to help account for yield variability and provide insight into improving production. This study was conducted to investigate the relationship of profile apparent soil electrical conductivity (EC_a) and topographic measures to grain yield for three contrasting soil–crop systems. Yield data were collected with combine yield-monitoring systems on three fields [Colorado (Ustic Haplargids), Kansas (Cumuic Haplustoll), and Missouri (Aeric Vertic Epiaqualfs)] during 1997–1999. Crops included four site-years of corn (*Zea mays* L.), three site-years of soybean (*Glycine max* L.), and one site-year each of grain sorghum [*Sorghum bicolor* (L.) Moench] and winter wheat (*Triticum aestivum* L.). Apparent soil electrical conductivity was obtained using a Veris model 3100 sensor cart system. Elevation, obtained by either conventional surveying techniques or real-time kinematic global positioning system, was used to determine slope, curvature, and aspect. Four analysis procedures were employed to investigate the relationship of these variables to yield: correlation, forward stepwise regression, nonlinear neural networks (NNs), and boundary-line analysis. Correlation results, while often statistically significant, were generally not very useful in explaining yield. Using either regression or NN analysis, EC_a alone explained yield variability (averaged over sites and years $R^2 = 0.21$) better than topographic variables (averaged over sites and years $R^2 = 0.17$). In six of the nine site-years, the model R^2 was better with EC_a than with topography. Combining EC_a and topography measures together usually improved model R^2 values (averaged over sites and years $R^2 = 0.32$). Boundary lines generally showed yield decreasing with increasing EC_a for Kansas and Missouri fields. Results of this study can benefit farmers and consultants by helping them understand the degree to which sensor-based soil and topography information can be related to yield variation for planning site-specific management.

YIELD MONITORING and mapping have given producers a direct method for measuring spatial variability in crop yield (Lark and Stafford, 1996; Pierce and Nowak, 1999). Yield maps have shown high-yielding areas to be as much as 150% higher than low-yielding areas (Kitchen et al., 1999) and have revolutionized the way producers view yield as they seek to learn how they might improve production. However, yield maps are confounded by many potential causes of yield variability (Pierce et al., 1997) as well as potential error sources from combine yield sensors (Lamb et al., 1995; Blackmore and Marshall, 1996). When other georeferenced information is available, producers naturally want to know if and how these various layers of data can be analyzed to help explain yield variability and provide insight into improving production practices.

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Along with yield mapping, producers have expressed increased interest in characterizing soil and topographic variability (Wiebold et al., 1998). Numerous properties influence the suitability of soil as a medium for crop root growth and yield. These include soil water-holding capacity, water infiltration rate, texture, structure, bulk density, organic matter, pH, fertility, soil depth, topography features (i.e., slope, aspect, etc.), the presence of restrictive soil layers, and the quantity and distribution of crop residues. These properties are complex and vary spatially (and with some, temporally) within fields. No single measurement adequately describes the influence of the soil environment on rooting and crop growth and yield. Georeferenced soil sampling for fertility status, typically from the surface layer from 0 to 20 cm, is often used by producers in developing recommendation maps for variable-rate fertilizer application. Information obtained from these samples [including fertility, organic matter, cation exchange capacity (CEC), and texture] has also been used in some research to evaluate yield variation (Kravchenko and Bullock, 2000; Nolin et al., 2001; Ward and Cox, 2001), but usually little or no significance has been found.

Inexpensive and accurate methods for measuring within-field soil variation would have the potential to greatly improve site-specific crop management. Sensors are ideal for mapping soil properties because they can provide data without the need to collect and analyze samples and can be linked to global positioning systems (GPS) and computers for on-the-go spatial data collection. Sensors that measure soil properties could play an important role in helping to characterize yield variation.

One sensor-based measurement that has shown promise is EC_a, which is a measure of the ability to conduct electrical current through the soil profile. Several authors have reported on relating EC_a to variation in crop production caused by soil differences (Jaynes et al., 1995; Kitchen et al., 1999; Luchiari et al., 2001; Zhang and Taylor, 2001). Rapid spatial measurement of EC_a can be accomplished using noncontact electromagnetic induction sensors (McNeil, 1992; Jaynes et al., 1993; Sudduth et al., 2001) or with direct-contact sensors such as rolling coulters that measure electrical resistance directly (Lund et al., 1999; Sudduth et al., 1999). In general, EC_a can be affected by a number of different soil properties, including clay content, soil water content (Kachanoski et al., 1990; Morgan et al., 2001), varying depths of conductive soil layers, temperature, salinity,

Abbreviations: CEC, cation exchange capacity; DEM, digital elevation model; EC_a, apparent soil electrical conductivity; $EC_{a\text{-}dp}$, deep (100 cm) apparent soil electrical conductivity; $EC_{a\text{-}sh}$, shallow (30 cm) apparent soil electrical conductivity; GPS, global positioning system; MLR, multiple linear regression; MQR, multiple quadratic regression; MQR_{+Int}, multiple quadratic regression including two-way linear interactions; NN, neural network.

organic compounds, and metals (Geonics Limited, 1992, 1997). Because many of these factors impact plant growth, EC_a measurements can be used on some soils as a surrogate measure of more costly soil chemical and physical measurements (Jaynes, 1996; Clark et al., 2001; Hartsock et al., 2001). For example, EC_a has been found to be highly correlated with claypan topsoil thickness (i.e., depth to the Bt horizon) (Doolittle et al., 1994; Sudduth et al., 2001). This soil property causes variation in infiltration and water storage characteristics for claypan soils (Jamison et al., 1968) and thus is a property that explains yield variation for average and below-average precipitation crop years (Kitchen et al., 1999).

Field topography plays an important role in the hydrological response of rainfall catchment and has a major impact on water availability for crop production in rainfed agriculture (Timlin et al., 1998; Kravchenko and Bullock, 2000). The introduction of real-time kinematic (RTK) GPS receivers has made possible automated collection of highly accurate elevation data, thus providing an efficient way of obtaining high-resolution digital elevation models (DEMs) of agricultural fields (Clark and Lee, 1998). The increasing availability of DEMs and advent of computerized terrain analysis tools have made it possible to readily quantify the topographic attributes of a landscape (Bell et al., 1995; Weibel and Heller, 1991).

Numerous techniques have been applied for understanding the relationship between crop yields and measured soil and site parameters. However, producers (and researchers for that matter) are still uncertain which analyses to use, how to interpret results, or both. Correlation and other linear techniques have often been reported in the literature (Sudduth et al., 1996; Kravchenko and Bullock, 2000). In most cases, linear analyses alone have failed to produce good functional models explaining yield variability. More complex parametric regression techniques, both linear and nonlinear, can be applied to the problem of relating crop yield to site and soil characteristics. The greatest difficulty in applying these methods is that they require the dependent variable be modeled as a function of the independent predictor variables. It is possible to introduce nonlinearity into the model, either explicitly or by pretreatment of the variables, but the fact remains that the functional form of the relationship between the dependent and independent variables must be assumed.

Nonlinear, nonparametric methods are an attractive alternative to parametric methods because they require only a few general assumptions about the form of the regression surface. For example, Sudduth et al. (1996) reported high accuracies when relating site and soil properties to crop yield using a nonlinear, nonparametric method known as projection pursuit regression (Friedman and Stuetzle, 1981). The feed-forward back-propagation NN is another nonlinear, nonparametric method that has received considerable attention as a general function approximation tool. Neural networks consist of a number of highly interconnected, simple processing units, or neurons, whose weights can be adjusted through an error back-propagation training algorithm to approximate the behavior of the input data. A pedagogy of NNs, while beyond the scope of this document, can be found in Rumelhart and McClelland (1986). Drummond et al. (1998) found several NN algorithms that were able to relate crop yield to soil and topographic properties with a high degree of accuracy while minimizing the risk and effects of overfitting. Further work over multiple site-years of crop yields indicated that neural methods could be effective function approximation tools, without loss of generalization ability, given appropriate training algorithms, network sizes, and learning parameters (Drummond, 1998; Drummond et al., 2000).

Another technique that has been used to develop relationships of yield to soil properties is boundary-line analysis. It is a procedure that rests on the idea that there are limits in response to factors in any situation (Webb, 1972). Boundary-line analysis is unique because it isolates a subset of the total data set for analysis. It assumes there is a significant biological response between a potential limiting factor of interest and a response variable, to imply a cause-and-effect relationship (Webb, 1972; Lark, 1997). A review of applications of this analysis has been reported previously (Kitchen et al., 1999). In general, the analysis identifies a subset of points lying on the upper edge of a large data set displayed in a two-dimensional scatter plot for some factor of interest and yield. A line is fit to this subset of points to develop a response function of that factor to yield. This upper boundary then represents, for the conditions of that data set, the maximum possible response to that limiting factor, and points below the boundary line represent conditions where other factors have limited the response variable (i.e., yield). The analysis works best when data sets are large, such as with spatially dense yield data obtained from combine yield monitoring.

We believe that sensor measurements of EC_a and topography from GPS can be used as indirect measures of soil property variation that will be associated with the variation observed in yield maps. Objectives of this research were to (i) investigate how well EC_a and topographic attributes related to grain yield for three contrasting soil–crop systems, (ii) compare interpretations from various statistical procedures when relating EC_a and topographic data to yield data, and (iii) assess differences in interpretations between individual years of yield data and yield data averaged over multiple years.

MATERIALS AND METHODS

Sites Description

Three fields with contrasting soils and climate were selected for this study. Table 1 provides field location and size, soil types, and cropping history information for 1997–1999. The study fields contrast in soil type, with fine sand to sandy loam in Colorado, silt loam in Kansas, and silt loam to silty clay in Missouri. Precipitation and soil age increases moving from west (Colorado) to east (Missouri). Corn was grown continuously under center-pivot irrigation, and annual tillage was used to manage the large amounts of residues generated on the Colorado field. The nonirrigated Kansas and Missouri fields were planted no-till, and crops were rotated for optimal soil water storage and to disrupt pest cycles.

Table 1. Location, cropping, and apparent soil electrical conductivity (EC_a)–sensing information for the study fields.

	Colorado	Kansas	Missouri
Field location			
County	Morgan	Saline	Boone
UTM† zone	NAD‡ 83, Zone 13N	NAD 83, Zone 14N	NAD 83, Zone 15N
Easting, m	582 600	634 200	573 600
Northing, m	4 465 000	4 294 900	4 343 100
Field size, ha	36	18	13
Predominant soils	Bijou (Ustic Haplargids) Valentine (Typic Ustipsamments)	Hord (Cumuic Haplustoll) Longford (Udic Argiuistoll)	Mexico (Aeric Vertic Epiaqualfs) Adco (Vertic Albaqualfs)
Average annual precipitation, mm	328	759	1026
Average May–Sept. temperature, °C	19.8	23.2	21.6
Cropping practices			
1997	Disk, rip, mulch/tread plant 76-cm rows, corn	Minimum till, wheat, 19-cm rows	No-till, planter, corn, 76-cm rows
1998	Disk, rip, mulch/tread plant 76-cm rows, corn	No-till, milo, 19-cm rows	No-till, drill, soybean, 19-cm rows
1999	Disk, rip, mulch/tread plant 76-cm rows, corn	No-till, soybean, 19-cm rows	No-till, drill, soybean, 19-cm rows
Date of EC_a sensing	March 1999	November 1997	October 1999
Soil conditions for EC_a sensing	After disking in spring, soil profile generally moist	Post double-cropped soybean; surface soil moist	Postharvest, soil profile generally dry

† UTM, Universal Transverse Mercator.
‡ NAD, North American Datum.

Apparent Soil Electrical Conductivity, Topography, and Yield Data Collection

The EC_a for each field was measured on a single date (dates shown in Table 1) using the Veris model 3100 sensor cart system manufactured by Veris Technologies of Salina, KS (Lund et al., 1999). This sensor identifies soil variability by directly sensing EC_a. As the cart is pulled through the field, a pair of coulter electrodes transmit an electrical current into the soil while two other pairs of coulter electrodes measure the voltage drop. The system georeferences the conductivity measurements using an external differential GPS receiver and stores the resulting data digitally. The coulter electrodes of the Veris 3100 are configured as a Wenner array, an arrangement commonly used for geophysical resistivity surveys. The sensor response to EC_a varies as a nonlinear function of depth. The measurement electrodes are configured to provide both shallow ($EC_{a\text{-sh}}$) and deep ($EC_{a\text{-dp}}$) readings of EC_a. With $EC_{a\text{-sh}}$, 90% of the response is obtained from the soil above the 30-cm depth. With $EC_{a\text{-dp}}$, 90% of the response is obtained from the soil above the 100-cm depth (Sudduth et al., 2003).

The EC_a data for the study fields were collected on transects approximately 20 m apart. Location and EC_a data were recorded on 1-s intervals, which corresponded to a measurement about every 2 to 3 m along the transects. General soil moisture conditions at the time of EC_a sensing are described in Table 1. The EC_a was kriged following generally accepted procedures (Birrell et al., 1996) to a 10-m grid and mapped (Fig. 1).

Elevation data for the Colorado site were collected using conventional surveying techniques with a vertical accuracy of 6 cm. A real-time kinematic GPS survey was used to collect elevation data on approximately 20-m transects for the Kansas and Missouri sites (vertical accuracy of 3–5 cm). The data from each site were kriged, using appropriate semivariograms, to create a DEM on a 10-m grid. Slope, profile curvature, and aspect were then calculated from this DEM using classical terrain-modeling algorithms (Surfer v7, Golden Software,

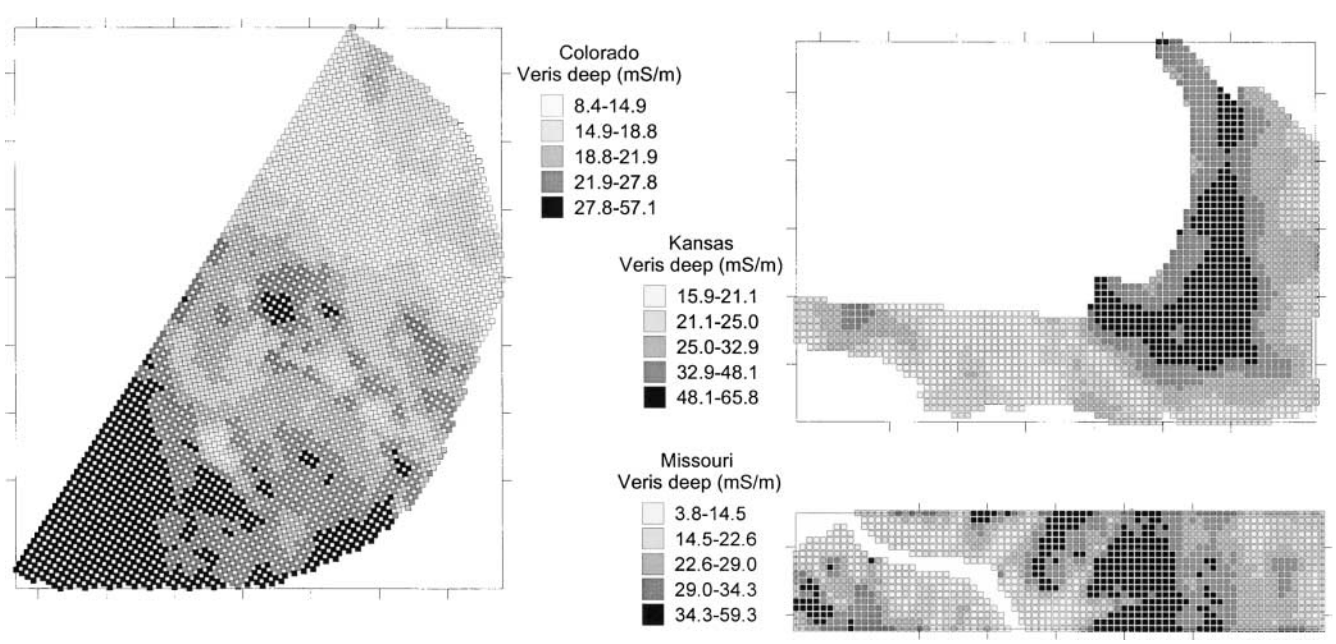

Fig. 1. Apparent soil electrical conductivity maps of the study fields.

Golden, CO). For the terrain attribute of aspect, we were most interested in whether north-facing slope affected yield differently than south-facing slope (not east vs. west). Therefore, aspect was modified to consider only its north-south facing effects, with 0° representing north facing and 180° representing south facing.

Combines equipped with commercially available yield-sensing systems were used to obtain data for 1997–1999 yield maps. Individual data points where yield data were unreliable were removed. Points may have been rejected due to any one or a combination of the following factors: significant positional errors, abrupt changes in operating speed, significant ramping of grain flow when entering and leaving the crop, a partial swath width of crop entering the combine, and instantaneous yield values outside reasonable bounds. Precise *threshold* values for rejection depended on the field, crop type, and individual combine yield monitoring system used to collect each data set. Our intent was to err on the side of caution, removing any questionable data from the point data set so that the interpolation procedure would not be significantly skewed by a few outliers. Yield data were then processed using geostatistics, and appropriate semivariogram models and parameters were used to krige the data to the same 10-m grid as EC_a and topographic data. All analyses were conducted on the grid data.

The following procedure was used to calculate a 3-yr average yield for the fields. First, each site-year was normalized by dividing the yield from each cell by the overall average yield from all of the cells within that site-year. This produced a distribution with a mean of 1 and a theoretical range of zero to infinity though in practice, a field with a range larger than 0 to 3 would be unusual. The three normalized yield values for each location were then averaged. This method allowed for averaging not only across multiple site-years, but also across multiple crop types.

Data Analysis

Four different types of analyses were performed to examine the relationship between yield and EC_a or topographic properties. The first three analytical procedures (correlation, regression, and NN) provide results where errors are minimized over the whole population. The fourth procedure (boundary-line analysis) is unique in that it identifies a subset of the data for interpretation.

Pearson correlation coefficients (r) were calculated between EC_a or topographic properties and between yield and EC_a or topographic properties. Forward stepwise multiple-regression models were used to assess the additive effects of soil and topographic properties on yield. With this forward stepwise method, terms already in the model do not necessarily stay. After a significant term was added, all of the variables in the model were retested with an F-test statistic to ensure continued significance ($P \leq 0.05$). If a term was no longer significant, it was removed from the model. From this iterative stepwise procedure, terms in the final model were all F-test significant, and all excluded terms were not significant. Regressions were conducted first considering only linear terms, then linear and quadratic terms, and finally linear, quadratic, and two-way linear interaction terms. The regression analysis considered three different combinations of EC_a and topographic data as candidate independent variables: (i) EC_a ($EC_{a\text{-sh}}$ and $EC_{a\text{-dp}}$), (ii) topography (elevation, slope, curvature, and aspect), and (iii) EC_a and topography combined. The number of independent variables considered in each type of stepwise regression analysis is provided in Table 2. Coefficients of determination (r^2 or R^2) for the regression models are reported.

Table 2. Number of candidate independent variables for stepwise regression of yield as function of apparent soil electrical conductivity (EC_a) and topographic properties. Regression analyses were performed for three different groupings of independent variables.

Group	Number of candidate variables†		
	MLR	MQR	MQR_{+Int}
Soil EC_a	2	4	5
Topography	4	8	14
EC_a + topography	6	12	27

† MLR, stepwise multiple linear regression; MQR, stepwise multiple quadratic regression; MQR_{+Int}, MQR with two-way linear interactions.

The use of NNs for this study was intended to provide a nonlinear, nonparametric statistical technique for comparison. As such, our goal was to provide a reasonable estimate of the prediction accuracy that could be achieved while guarding against significant overfitting of the independent data and without the implementation of an extremely time-consuming cross-validation approach. For NN applications, there are several parameters that must be considered, all of which may have a significant impact on the network's accuracy and generalization abilities. These parameters include network size, topology, training algorithm, training algorithm parameter selection, and amount of training time. A previous study by Drummond (1998) on a number of similar data sets provided a good basis for selecting these parameters. A fully connected feed-forward network with an input layer of up to nine inputs, a single hidden layer consisting of 10 neurons, and a single output neuron was selected. This provided enough flexibility to achieve a good fit while limiting the possibility of overfitting. A training algorithm known as resilient back-propagation, or rprop (Reidmiller and Braun, 1993), produced rapid learning with good generalization results in all test cases. The algorithm was allowed to train for 5000 iterations because on similar test sets, optimal generalization results had been achieved in every test case by this point, with little indication of overfitting between achieving the optimal solution and 5000 iterations. Yield, EC_a and topography data sets for each field and predictor variable grouping were analyzed using the NNs described above. The trained networks were used to estimate crop yield and evaluate goodness of fit.

The relationship between yield and EC_a on these data sets was also explored using an upper *boundary-line* procedure, similar to that described by Kitchen et al. (1999). For this specific boundary-line analysis, we examined the relationship of yield to $EC_{a\text{-dp}}$ for each of the three fields and for all 3 yr and also provided a few selected examples of boundary-line analysis between elevation and yield. While we recognize that EC_a and elevation are not direct measures of yield-limiting factors, they are indirect measures of numerous soil properties that have an impact on crop growth. For the analysis, ordered EC_a or elevation values, from lowest to highest, were divided into $N/60$ bins [where N = number of paired yield–EC_a (or yield–elevation) measurements for a site-year] and processed so that each bin contained approximately 60 paired measurements. In each bin, data above the 95th percentile of yield were selected to represent the *upper edge* and included in a data subset. Linear, quadratic, and cubic terms of $EC_{a\text{-dp}}$ or elevation (as well as the inverse functions of these two) were evaluated using least-squares regression on the boundary data subset. The lowest order/highest R^2 model was selected.

Table 3. Descriptive statistics for apparent soil electrical conductivity and topographic properties of the three study fields.

Statistic	Field	N	$EC_{a\text{-}sh}$†	$EC_{a\text{-}dp}$‡	Elevation	Slope	Curvature	Aspect§
			mS m^{-1}		m	degrees	10^{-2} m	degrees
Mean	Colorado	3272	12.8	22.4	1356.0	0.63	0.000006	81.3
	Kansas	1784	12.9	33.2	349.8	0.95	0.000098	98.5
	Missouri	1304	16.4	25.4	261.5	1.09	0.000022	78.9
Standard deviation	Colorado	3272	4.6	9.2	0.52	0.43	0.000402	47.8
	Kansas	1784	3.5	13.4	1.1	0.64	0.001190	45.2
	Missouri	1304	7.2	10.3	2.2	0.65	0.000624	53.3
Minimum	Colorado	3272	4.0	8.4	1354.0	0.03	−0.003250	0.1
	Kansas	1784	7.8	15.9	347.9	0.02	−0.007050	0.0
	Missouri	1304	2.8	3.8	257.5	0.04	−0.001950	0.1
Maximum	Colorado	3272	38.2	57.1	1357.0	2.67	0.002660	180.0
	Kansas	1784	30.3	65.8	352.5	3.68	0.006200	179.5
	Missouri	1304	45.7	59.3	264.7	3.24	0.005550	179.9

† $EC_{a\text{-}sh}$, shallow (30 cm) apparent soil electrical conductivity.
‡ $EC_{a\text{-}dp}$, deep (100 cm) apparent soil electrical conductivity.
§ Degrees from true north.

RESULTS AND DISCUSSION

Within-field variation in EC_a and topographic properties for the three sites are compared in Table 3. Most properties can be compared across sites because sampling and analysis procedures were common. However, EC_a has been shown to have significant temporal variability, primarily as the result of changes in soil profile moisture amount and distribution (Sudduth et al., 2001). Therefore, comparing EC_a across various sites, whether the sites are similar or dissimilar in soil type, may be misleading. A few contrasts of the other soil parameters are notable. Average slope for the three fields was higher for Kansas and Missouri fields than for the Colorado field. Because the Colorado field is generally flat and very well drained, little surface runoff occurs on this field. Runoff with erosion occurs occasionally on the Kansas field and often on the Missouri field, the result of greater slope, higher precipitation, and a finer-textured soil.

Correlation Analysis

Single-factor correlation analysis tools are commonly found in software used by producers and their consultants to evaluate spatial data. Correlations between EC_a or topographic properties (Table 4) and between yield and EC_a or topographic properties (Table 5) are provided. With relatively large data sets (as in this case), statistically significant correlations were common. More than 60% of the correlation coefficients in Table 4 and more than 80% of the correlation coefficients in Table 5 were significant ($P = 0.01$). However, a factor could be found to be significant even with a quite low correlation. For example, 36% of the significant correlations for yield and EC_a or topographic properties from the Colorado field (the field with the largest number of data points) had weak and quite meaningless coefficient values $\leq$0.10. Single-factor correlation analysis provides very little direct evidence for the cause(s) of yield variation. Unless the data are transformed, correlations only assess the linear relationship between variables. Additionally, variation in yield data is the result of multiple and interacting factors (Sudduth et al., 1996). For these reasons, we advocate that if correlation analysis is used to compare yield and soil property data, the results should be viewed subjectively and mainly used as an indicator of those factors to be included in more scrutinizing analyses.

When considering EC_a and topographic properties, the highest correlation coefficients were found between the two EC_a measurements (Table 4). Significant correlation coefficients were consistently detected between EC_a and the topographic attributes of slope and aspect. Also, for Colorado and Missouri fields, both EC_a measurements were positively correlated with soil CEC (r values between 0.55 and 0.88), and $EC_{a\text{-}sh}$ was positively correlated with soil organic matter (r values $\geq$ 0.80) (CEC and soil organic matter data not shown). Correlations between topographic properties and CEC or soil organic matter were low (r values < 0.25) for the Colorado field. For Missouri, slope and aspect were positively correlated with CEC and organic matter (r values between 0.36 and 0.56).

Correlation coefficients between EC_a or topographic properties and yield were generally much lower for the Colorado field compared with the other two fields (Table 5). Using coefficient of variation as a measure of field yield stability within years, yield for the Colo-

Table 4. Pearson correlation coefficients between apparent soil electrical conductivity and topographic properties.

	$EC_{a\text{-}sh}$†	$EC_{a\text{-}dp}$‡	Elevation	Slope	Curvature
	Pearson coefficient, r				
Colorado					
$EC_{a\text{-}dp}$	0.77*				
Elevation	−0.01	0.05*			
Slope	−0.25*	−0.28*	0.04		
Curvature	−0.02	0.05*	0.01	−0.01	
Aspect§	−0.20*	−0.13*	−0.03	0.06*	0.04
Kansas					
$EC_{a\text{-}dp}$	0.75*				
Elevation	0.27*	0.09*			
Slope	0.45*	0.42*	0.34*		
Curvature	0.02	0.01	−0.22*	−0.03	
Aspect§	0.09*	0.18*	0.08*	−0.05	−0.03
Missouri					
$EC_{a\text{-}dp}$	0.79*				
Elevation	0.03	0.37*			
Slope	0.30*	0.12*	−0.48*		
Curvature	−0.06	−0.18*	−0.30*	0.01	
Aspect§	0.41*	0.26*	−0.13*	0.01	−0.05

* Significant (test for $|r| = 0$) at $P \leq 0.01$ level.
† $EC_{a\text{-}sh}$, shallow (30 cm) apparent soil electrical conductivity.
‡ $EC_{a\text{-}dp}$, deep (100 cm) apparent soil electrical conductivity.
§ Degrees from true north.

Table 5. Pearson correlation coefficients between grain yield and apparent soil electrical conductivity and topographic properties.

	EC_{a-sh}†	EC_{a-dp}‡	Elevation	Slope	Curvature	Aspect§
Colorado	Pearson coefficient, *r*					
1997	0.20*	0.41*	0.17*	−0.14*	0.10*	−0.05*
1998	−0.10*	0.06*	0.20*	−0.04*	0.04	−0.02
1999	0.14*	0.22*	0.08*	−0.10*	0.07*	−0.03
3-yr mean	0.09*	0.26*	0.18*	−0.11*	0.08*	−0.04
Kansas						
1997	−0.19*	−0.14*	−0.33*	−0.18*	−0.03	0.00
1998	−0.25*	−0.16*	−0.35*	−0.26*	0.00	0.07*
1999	−0.68*	−0.72*	−0.10*	−0.44*	0.05	−0.26*
3-yr mean	−0.61*	−0.57*	−0.36*	−0.46*	0.02	−0.13*
Missouri						
1997	−0.61*	−0.68*	−0.23*	−0.06	0.14*	−0.22*
1998	−0.10*	−0.09*	0.26*	−0.17*	0.02	0.00
1999	−0.22*	−0.32*	0.08*	−0.28*	0.04	0.04
3-yr mean	−0.43*	−0.50*	−0.02	−0.21*	0.09*	−0.08*

* Significant (test for $|r| = 0$) at $P \leq 0.01$ level.
† EC_{a-sh}, shallow (30 cm) apparent soil electrical conductivity.
‡ EC_{a-dp}, deep (100 cm) apparent soil electrical conductivity.
§ Degrees from true north.

rado field was more stable than for the Kansas and Missouri fields (Table 6). We attributed this yield stability in the Colorado field to the relatively fewer areas with either excessive soil water (i.e., well-drained soils resulting in minimal crop drowning) or water-deficient stress (due to irrigation). The effect of sprinkler irrigation on the Colorado field was that soil properties often associated with variations in soil water storage and distribution across the field (e.g., texture, slope, curvature) had much less influence on crop production than did the same properties under the nonirrigated production of the other two fields.

Apparent soil electrical conductivity consistently provided the highest correlation coefficients with yield though the value of the coefficient varied greatly from year to year. For example, correlation with EC_{a-dp} for the Kansas field was −0.14 for 1997 and −0.72 for 1999. In a few cases, correlation coefficients were positive one year and negative the next, such as seen with elevation and yield for the Missouri field in 1997 and 1998. These contrasting effects neutralize each other when examining the correlations for 3-yr averages (Table 5). Differences in crop type and climate can produce very different correlations from year to year (Sudduth et al., 1996; Kitchen et al., 1999; Kravchenko and Bullock, 2000). While the correlation coefficients of yield and EC_a were negative for Kansas and Missouri fields, they were mostly positive for the Colorado field. Increasing EC_a is often associated with increasing clay (McNeil, 1992). Because the soils on the Colorado field were generally well drained, we attribute this trend to slightly improved water-holding capacity with higher EC_a. For the other two fields, we speculate that higher EC_a is associated with factors such as poor internal soil drainage and high-clay-content subsoil that restricts root growth. For the Kansas field, slope and elevation were also important properties associated with yield variability (Table 5).

Table 6. Yield coefficient of variation (CV) for the three study fields.

Year	Colorado	Kansas	Missouri
	CV		
1997	0.10	0.22	0.31
1998	0.12	0.23	0.14
1999	0.12	0.31	0.34

Multiple-Regression Analysis

The EC_a and topographic properties were analyzed using stepwise multiple linear regression (MLR), stepwise multiple quadratic regression (MQR), and MQR including two-way linear interactions (MQR_{+Int}) regression. Parameters in the model were retested for significance after each regression step and were eliminated if not significant. While in the statistical sense, EC_a and/or topography *explained* yield variability, we note that the relationship between them is an indirect one. Agronomically, properties like topography and EC_a are not affecting yield directly; they are only measures of how water availability is affected, and this is at the root of yield variability. Coefficients of determination are given for each year and the 3-yr average for each field in Table 7. In general, R^2 values of MLR, MQR, and MQR_{+Int} increased in this same order. This is expected because the number of variables considered for inclusion increased in the same order.

Several trends could be found when examining which individual variables were included in the stepwise regressions. Out of the regression models represented in Table 7, the frequency of inclusion in a model (either as a linear, quadratic, or an interaction variable) was as follows: EC_{a-sh} (68%), EC_{a-dp} (70%), elevation (56%), slope (63%), curvature (45%), and aspect (55%). All six measurements were included for each field but not necessarily every year. Aspect entered into models less frequently for the Colorado field and curvature less frequently for the Missouri field. Variables that were correlated (Table 4) were still often both included in the models, indicating a unique relationship of each to yield.

As with the results for correlation, topography parameters provided little explanation of yield variability for the Colorado field, due to sprinkler irrigation. For the Kansas and Missouri fields, neither EC_a nor topographic measures alone explained yield variability very well [all $R^2 \leq 0.23$ in 2 out of the 3 yr (1997 and 1998 for Kansas

Table 7. Coefficient of multiple determination for yield as a function of apparent soil electrical conductivity (EC_a) and topographic properties. Models included only significant terms (*F*-test $P \leq 0.05$) for stepwise multiple linear regression (MLR), stepwise multiple quadratic regression (MQR), and MQR with two-way linear interactions (MQR_{+Int}). A nonlinear neural network (NN) analysis was also conducted. The EC_a and topographic properties were analyzed by three separate groups: (i) EC_a, (shallow and deep EC_a), (ii) topographic properties (elevation, slope, curvature, and aspect), and (iii) EC_a and topographic properties combined.

		Colorado				Kansas				Missouri			
Year	Group(s)	MLR	MQR	MQR_{+Int}	NN	MLR	MQR	MQR_{+Int}	NN	MLR	MQR	MQR_{+Int}	NN
		R^2											
1997	Soil EC_a	0.20	0.26	0.26	0.31	0.03	0.04	0.04	0.05	0.48	0.51	0.53	0.48
	Topography	0.04	0.05	0.07	0.17	0.13	0.17	0.19	0.25	0.17	0.27	0.30	0.54
	EC_a + topography	0.22	0.27	0.32	0.33	0.14	0.24	0.32	0.44	0.48	0.52	0.61	0.61
1998	Soil EC_a	0.06	0.14	0.14	0.17	0.07	0.13	0.14	0.08	0.01	0.04	0.05	0.12
	Topography	0.02	0.03	0.04	0.18	0.16	0.18	0.23	0.27	0.08	0.10	0.14	0.29
	EC_a + topography	0.08	0.16	0.20	0.25	0.17	0.19	0.31	0.28	0.13	0.16	0.26	0.35
1999	Soil EC_a	0.05	0.07	0.07	0.12	0.57	0.59	0.59	0.63	0.10	0.13	0.22	0.20
	Topography	0.02	0.03	0.03	0.07	0.28	0.29	0.34	0.52	0.08	0.10	0.12	0.18
	EC_a + topography	0.06	0.07	0.08	0.16	0.61	0.68	0.76	0.83	0.22	0.26	0.40	0.40
3-yr	Soil EC_a	0.10	0.17	0.17	0.23	0.40	0.43	0.43	0.46	0.25	0.27	0.35	0.40
	Topography	0.03	0.05	0.06	0.17	0.28	0.29	0.30	0.45	0.07	0.10	0.14	0.39
	EC_a + topography	0.13	0.19	0.23	0.32	0.47	0.50	0.54	0.56	0.30	0.36	0.45	0.46

and 1998 and 1999 for Missouri)]. But in 1999 (soybean) for Kansas and in 1997 (corn) for Missouri, between 50 and 60% of yield variability was explained using only the two EC_a measurements. For both of these crop years, summer precipitation was average or below average. For Missouri in 1997, July precipitation was only 25% of average (85 mm deficient from average), resulting in crop water stress during pollination. Under these dry conditions, the soil's ability to store water was the main influence on yield variability. Areas of these two fields with highest EC_a readings were defined as upland and sideslope soils that have either a well-defined Bt horizon (and therefore greater profile clay content) or a shallower Bt horizon. For claypan soils such as were found at the Missouri field, EC_a has been used to predict depth to the restrictive claypan horizon (Doolittle et al., 1994; Sudduth et al., 1995), a property that mediates potential plant-available water capacity and limits crop yield for these soils in average to below-average precipitation years (Thompson et al., 1991; USDA-NRCS, 1995).

Apparent soil electrical conductivity and topography variables were also considered collectively using stepwise regression analysis. These measures can be obtained rapidly by on-the-go sensors and can even be collected simultaneously. In almost all cases, there was an improvement in accounting for yield variability when allowing both EC_a and topography terms into the model selection process over EC_a or topography alone. The greatest improvement in R^2 values was seen when interactions (MQR_{+Int}) were also considered (see Kansas 1997 and 1999 and Missouri 1999 in Table 7). While there can be significant and high correlation between EC_a and topographic properties (Table 4), the comparison of R^2 values from these regressions (that include interactions and quadratic relationships) supports our point again that each of these measures can uniquely contribute to modeling yield variability.

Regressions for 3-yr average yields are also given in Table 7. While an understanding of long-term relationships is desired, averaging across crops and years may result in interpretations that are crop or year specific. For Kansas and Missouri, the 3-yr average regression coefficients were greatly influenced by one out of three crop years—1999 Kansas soybean and 1997 Missouri corn. Yield variation will vary from year to year and crop to crop as affected by soil properties (Colvin et al., 1997; Sudduth et al., 1997; Kravchenko and Bullock, 2000). While we conducted the 3-yr average regression analysis, averaging yield maps may neutralize the information needed to better understand the interaction between soil or topographic properties and climate for crop production (Sawyer, 1994). With our study, averaging site-years was the safest for the Colorado site because the crop grown was unchanged and was under irrigation over the three years.

We have heard producers say they would like to use these EC_a and topographic property measurements in developing productivity *management zones* in their fields. These regression results indicate that all six measurements, along with their interactions, were helpful in accounting for yield variability, but the measurements that were most helpful varied year to year. In some years, topography information best accounted for yield variation; in other years, EC_a was more important (Table 7). As such, there is no clear indication that any of these measurements we considered ought to be discounted when attempting to create productivity management zones.

Neural Network Analysis

Neural networks were generally quite capable of estimating crop yield from EC_a and topographic parameters. Figure 2 shows one example for the 1999 Kansas site. Note that in this case, the spatial crop variation patterns are reliably replicated, with approximately 86% of the variation in actual crop yield explained by the model. Other site-years showed somewhat lower accuracies (Table 7); however, only three of the nine site-years produced results poorer than 30% when all predictor variables were available to the model. Accuracies on the 3-yr normalized data sets were all above 30% when all predictor variables were available. Comparing the goodness of fit between techniques is informative. The NN outperformed MLR in all but one case and outperformed MQR in all but two cases. While more similar,

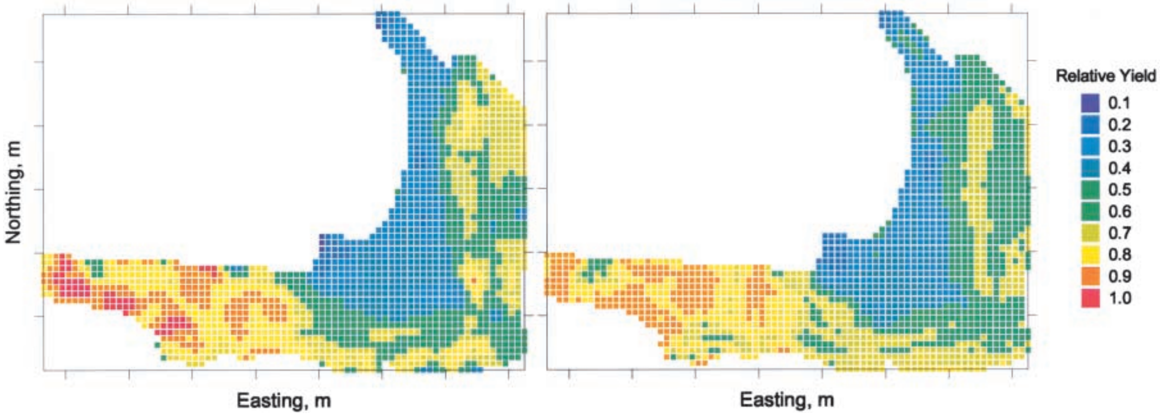

Fig. 2. Actual (right) and neural network (left)–estimated yields for the Kansas 1999 site-year.

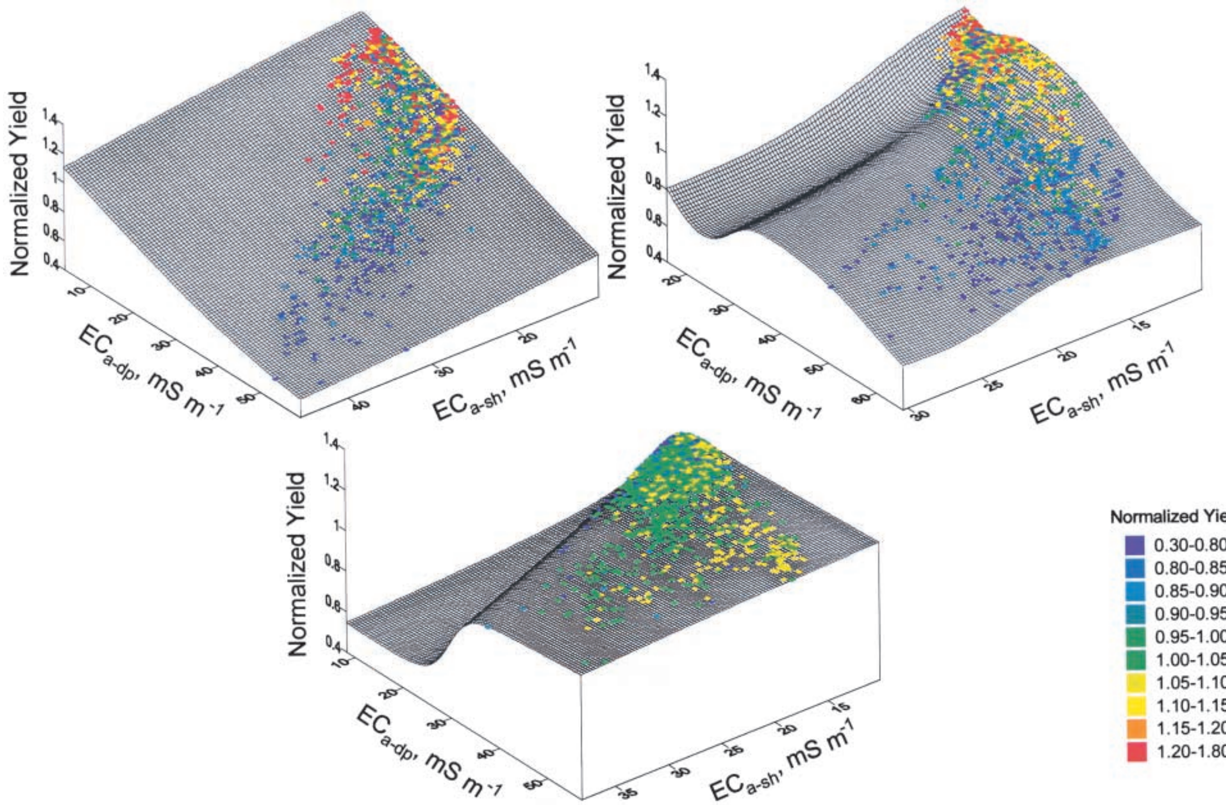

Fig. 3. Three-year yield response to shallow ($EC_{a\text{-}sh}$) and deep ($EC_{a\text{-}dp}$) apparent soil electrical conductivity modeled by neural network analysis for (top left) Missouri, (top right) Kansas, and (bottom) Colorado fields.

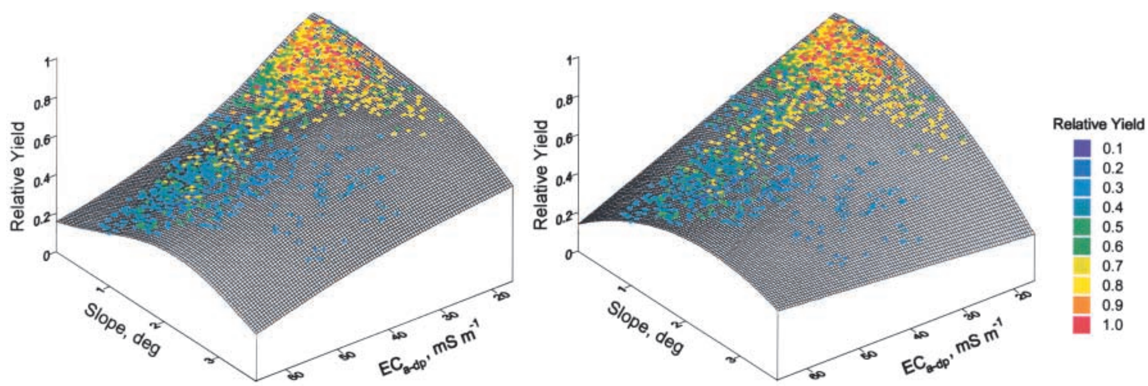

Fig. 4. Yield response to deep apparent soil electrical conductivity ($EC_{a\text{-}dp}$) and slope for the Kansas 1999 site-year based on (left) neural network and (right) multiple quadratic regression including two-way linear interactions models.

the NN outperformed MQR_{+Int} in the vast majority of cases.

The fact that an empirical model can accurately fit yield data to soil and topographic characteristics is of interest, but more interesting is how it does so. Figure 3 shows the results of NN modeling of the 3-yr normalized yield data, using only the EC_a group for each of the three sites. The trained network was presented with a fine grid of observations representing the range of values for $EC_{a\text{-}sh}$ and $EC_{a\text{-}dp}$ found within the field. The resulting normalized yields (based on the range of yield values found within the field) represent the response surface for that two-input, one-output model. The actual training observations for these networks are draped over the surface, both for visual comparison and to show the region over which the model is defined. These surfaces provided quite useful information. For example, for both the Missouri and Kansas sites, which were nonirrigated, there was a general trend of decreasing yield with increasing EC_a, both for $EC_{a\text{-}sh}$ and for $EC_{a\text{-}dp}$. For the Missouri site, this relationship appeared to be quite linear in both dimensions, and on these claypan soils, the message was clear; soils with lower conductivity (and lower clay content) were more productive. While this general trend held for the Kansas site as well, there are ripples on the surface within the area of the data points that indicate that the relationship is somewhat more complex. The irrigated Colorado site, where the EC_a model provided the poorest fit, was also easy to interpret. Productivity was generally quite high and more stable between years, as is indicated by the vast majority of points being within 20% of maximum yield. Only in the areas where EC_a was high in the surface layer ($EC_{a\text{-}sh}$), combined with low conductivity below the surface layer ($EC_{a\text{-}dp}$) (interpreted as fine-textured soil over subsoil sand), was there a consistent, predictable reduction in yield. (Many of these points are not visible in Fig. 3 because axis orientation was held constant over locations.)

In general, the NN methods were able to provide the most accurate empirical models of the data. However, there are many (approximately 75%) of the cases where the NN did not increase coefficients of determination by more than 0.10 over MQR_{+Int}; thus, the relatively less complex model might well have been selected for the sake of parsimony. In general, the MQR_{+Int} model provided surfaces very similar in nature to those produced by the NN. Figure 4 shows an example for the EC_a plus topography variable set on the 1999 Kansas site. The values for $EC_{a\text{-}sh}$, elevation, aspect, and curvature were fixed to field average values, and a fine grid over the range of $EC_{a\text{-}dp}$ and slope variables was produced. This pattern set was then presented to the appropriately trained NN and MQR_{+Int} models, and resulting response surfaces were mapped. While there were some minor differences, the surfaces were very similar in overall shape, and both indicate that the most productive soils in the field were the soils with the lowest EC_a and the least amount of slope. However, as EC_a and clay content increased (McNeil, 1992), the optimum yields were found at slopes approaching 2° for both models. In short, low-EC_a (high sand) soils were more productive with little or no slope while high-EC_a (high clay) soils were more productive where soils had better surface drainage.

Boundary-Line Analysis

An examination of scatter plots from large data sets can be very helpful in understanding the nature of association between variables. Boundary-line analysis is merely a focus on the upper edge of the scatter-plot *data cloud*. This upper boundary represents, for the conditions of that data set, the maximum possible response to the factor used as the independent variable. Points below the boundary line represent conditions where other factors have limited the response of the dependent variable. Space limitations restrict us from showing all possible scatter plots of yield in association with soil and topographic properties. We have limited our presentation and analysis here to $EC_{a\text{-}dp}$ and yield for each site-year (Fig. 5–7) and a few other examples of boundary-line analysis using elevation and yield (Fig. 8). For each figure, data used to define the boundary lines

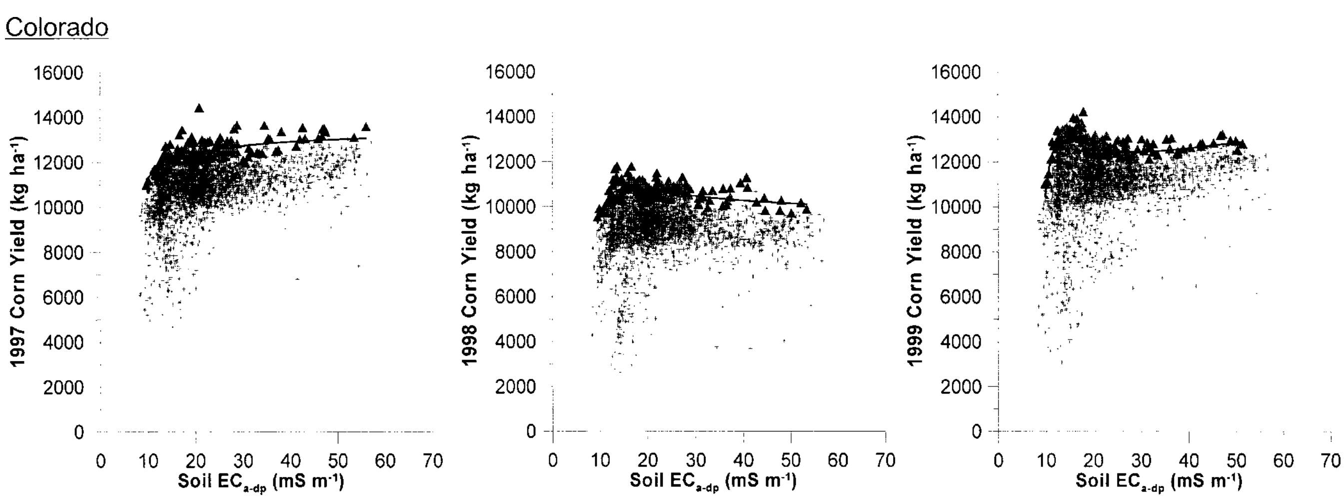

Fig. 5. Scatter plot and boundary line of yield vs. deep apparent soil electrical conductivity ($EC_{a\text{-}dp}$) for Colorado in 1997 to 1999. Points represented with triangles are yield data above the 95th percentile for each 60-point increment (or bin) of EC_a data.

Kansas

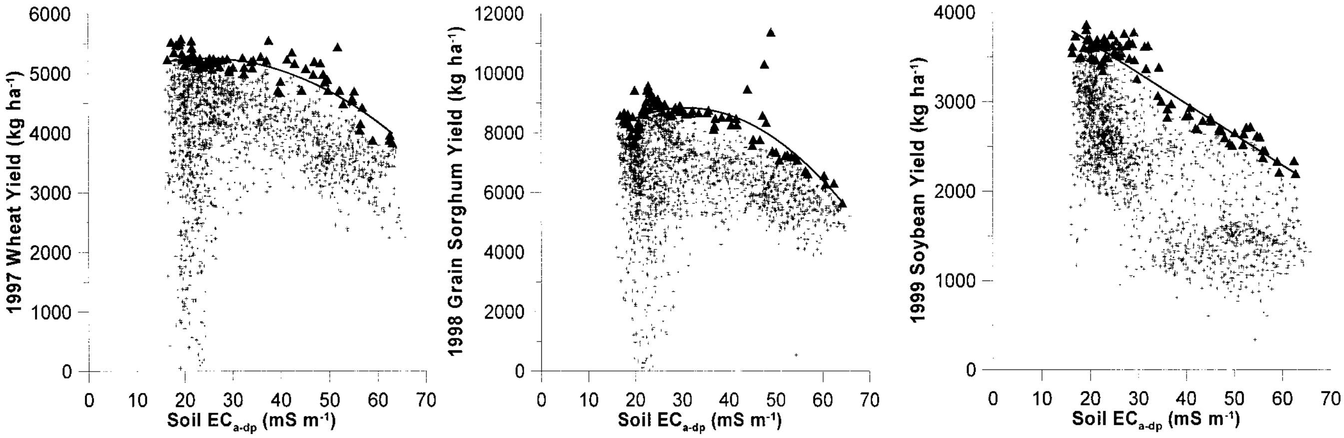

Fig. 6. Scatter plot and boundary line of yield vs. deep apparent soil electrical conductivity ($EC_{a\text{-}dp}$) for Kansas in 1997 to 1999. Points represented with triangles are yield data above the 95th percentile for each 60-point increment (or bin) of EC_a data.

are represented as larger points in the scatter plots. The regression models that best fit the upper boundary data are described in Table 8.

For Colorado, scatter plots and boundary lines were very similar in shape among years (Fig. 5). Lower R^2 values, compared with the other two fields, were associated with relatively small changes in yield (i.e., stable yield) over the observed range of EC_a. This relationship between yield stability and lower R^2 values was also observed in a previous boundary-line analysis (Kitchen et al., 1999). For all 3 yr, the greatest variation in yield was exhibited at lower $EC_{a\text{-}dp}$ values. As represented by the boundary line, corn yield for all 3 yr tended to diminish when $EC_{a\text{-}dp}$ was <15 mS m^{-1}. Lower $EC_{a\text{-}dp}$ areas on this field were high in sand content (data not included here) and would be most quickly depleted of soil moisture during peak crop water-use periods.

The regression models fit the upper boundary of $EC_{a\text{-}dp}$ and yield data best for the Kansas and Missouri fields (Table 8; Fig. 6 and 7). Boundary lines generally showed that yield decreased with increasing $EC_{a\text{-}dp}$. For the Missouri field, the higher $EC_{a\text{-}dp}$ areas were associated with thin topsoil (Doolittle et al., 1994; Sudduth et al., 1995). For the Kansas field, the higher $EC_{a\text{-}dp}$ areas were associated with sideslope and upland areas of the field. In a previous study on claypan soils, Kitchen et al. (1999) linked this type of boundary-line relationship with seasons having significant plant stress due to deficient plant-available water, particularly when the stress occurred during the crucial periods of flowering and seed set. No soil water measurements were made for these study fields, but those who managed the fields in Kansas and Missouri observed water stress during these seasons, especially in the areas higher in $EC_{a\text{-}dp}$. Yield tended to be more stable (i.e., less variable) as EC_a increased for the Kansas and Missouri fields. In some situations, yield was especially poor at low EC_a (e.g., see Kansas 1997 and 1998). In these areas, the producer noted poor crop stand, greater weed pressure, or both.

Three other examples of boundary-line analysis are shown, relating elevation and yield (Fig. 8). In the plot of Kansas 1999 soybean yield, the regression models tested did not fit the boundary data well, so a running average (window of five points) has been shown on the

Missouri

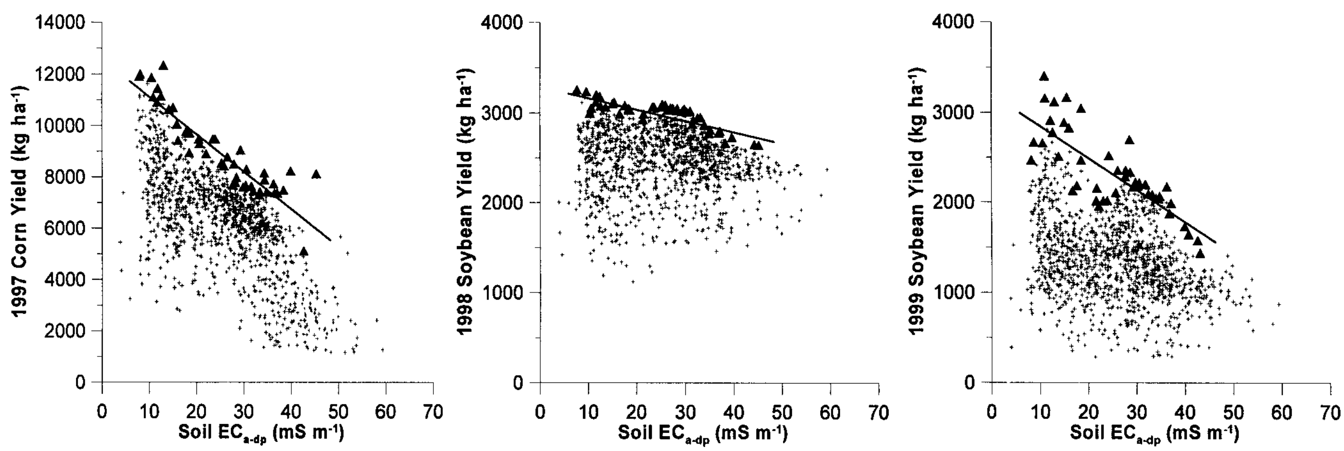

Fig. 7. Scatter plot and boundary line of yield vs. deep apparent soil electrical conductivity ($EC_{a\text{-}dp}$) for Missouri in 1997 to 1999. Points represented with triangles are yield data above the 95th percentile for each 60-point increment (or bin) of EC_a data.

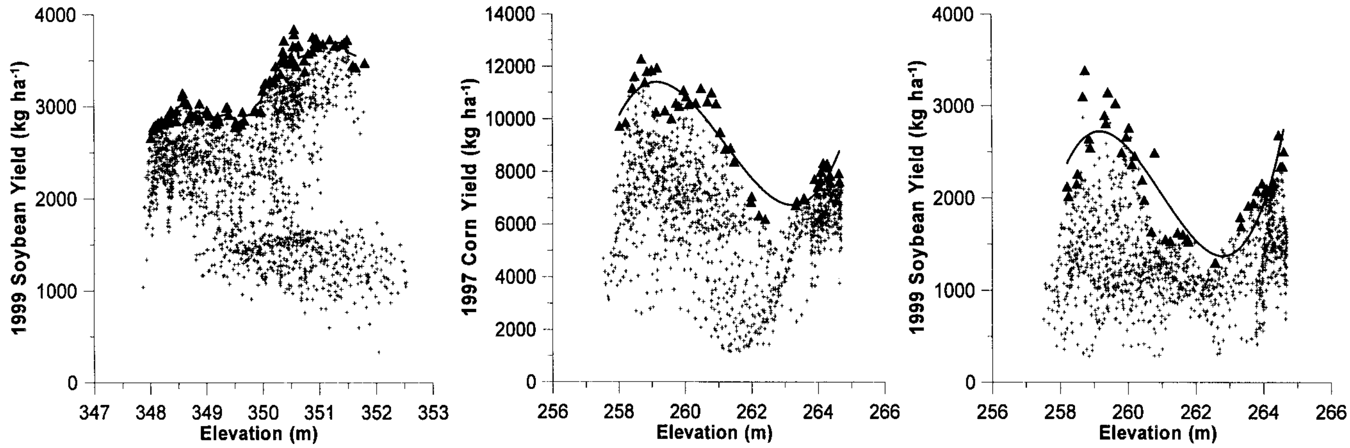

Fig. 8. Scatter plot and boundary line of yield vs. elevation for (left) Kansas 1999 soybean, (middle) Missouri 1997 corn, and (right) Missouri 1999 soybean. Points represented with triangles are yield data above the 95th percentile for each 60-point increment (or bin) of elevation data.

plot. For this plot, two distinctive clusters (or populations) of data are present. A similar phenomenon, although not quite as obvious, can be seen in the $EC_{a\text{-dp}}$ vs. yield scatter plot for the same crop year (Fig. 6). Though both of these data clusters are at about the same elevation, the upper cloud represents soil in the summit position of a landscape, and the lower cloud represents a sideslope soil that is part of a different landscape sequence. For the Missouri field in Fig. 8, corn and soybean yield potential, as represented by the boundary line, was consistently better in the lower elevation (toeslope) and upper elevation (summit) areas of the field where plant-available water is presumed to be much better. Yield was least on the midelevation sideslope areas of the field where topsoil was shallow and plant-available water reduced.

The dispersed nature of the data in all of the scatter plots (Fig. 5–8) is representative of the multiple yield-controlling factors that will inevitably be observed when examining crop production data collected over large areas. The numerous effects of soil, weather, management, and localized insect, weed, disease, and wildlife pressure on crop yield are all expressed in growing crop plants. The variability induced by these factors is much more than what EC_a or elevation alone can represent. The primary value of boundary-line analysis lies in its ability to delineate maximum yield relative to some other quantified property of interest. This, along with adequate yield records, may serve as a suggestion of yield potential. It is a diagnostic tool for delineating possible soil problems and estimating the magnitude of yield loss due to variation in the variable being examined. It also provides a picture of yield reduction due to the combined effects of other yield-limiting factors.

CONCLUSIONS

While producers and their consultants seem anxious to have streamlined and specific analytical procedures for relating mapped yield to soil and topographic variables, no single analytical technique is a panacea. Correlation analysis is most often used on these types of data sets. Yet, data showing a low but significant correlation can be rather intriguing and enlightening with another analysis [e.g., compare correlation results (Table 5) with boundary-line analysis results (Fig. 8) for Kansas 1999 soybean yield and elevation]. As indicated earlier, we caution against only using correlation analysis.

Visually examining the data in scatter plots (with or without a boundary line) demonstrates that multiple factors can affect yield, that the relationship between yield and soil properties can be nonlinear in nature, and that potential interactions between variables exist. Multiple groups of data, such as shown in Fig. 6 and 8 for Kansas 1999 soybean yield, were indicative of interacting variables. Only with more rigorous investigation were we able to isolate plausible causes (such as was illustrated with Fig. 4). Thus, a weakness of bound-

Table 8. Boundary-line regression results for the three study fields.

Scatter-plot data	Field	Year	*N* in boundary line	Regression type	r^2 or R^2
$EC_{a\text{-dp}}$†and yield	Colorado	1997	158	Inverse	0.50
		1998	158	Inverse cubic	0.34
		1999	158	Inverse cubic	0.50
	Kansas	1997	85	Quadratic	0.73
		1998	85	Quadratic	0.57
		1999	85	Linear	0.90
	Missouri	1997	46	Linear	0.83
		1998	46	Linear	0.83
		1999	46	Linear	0.63
Elevation and yield	Kansas	1999	85	Running average†	–
	Missouri	1997	46	Cubic	0.88
		1999	46	Cubic	0.69

† $EC_{a\text{-dp}}$, deep (100 cm) apparent soil electrical conductivity.
‡ A running average (window of five points) was used for boundary line since regression models tested did not fit the boundary data well.

ary-line analysis is that it is a single-factor analysis where interactions must be assumed to be insignificant at the boundary (Lark, 1997).

As measured by coefficient of determination, the MQR_{+Int} and NN procedures gave models that best explained yield variability. They were also the most complex, which made it difficult to isolate and explain specific effects of individual variables. Our approach to agronomically explain these models was to hold constant all but a few parameters and generate a response surface that could be evaluated graphically, such as shown in Fig. 3 and 4.

In some years, topography variables were best in accounting for yield variation, and in other years, EC_a was best. In a few cases, considering interactions between these two groups gave significant increases in the model R^2 values. While EC_a measurements were included in the models slightly more often than the topography measurements, both groups were important in helping account for yield variation.

When one is most interested in the effects of one or two soil variables, scatter plots with boundary-line analysis may be appropriate. While we have not attempted boundary-line analysis on points in a three-dimensional scatter plot, this approach seems reasonable if one is interested in interactions between two independent variables. If, on the other hand, the goal is to account for as much yield variation as possible, then complex analyses inclusive of multiple and interacting yield-limiting variables, such as MQR_{+Int} and NN procedures, may be most successful.

Regardless of the analytical procedure used, EC_a and topographic properties were important parameters in accounting for yield variability. While significant relationships between grain yield and these sensor-based soil properties were shown, climate, crop type, and specific field characterization information are generally required to interpret the relationship for any given site-year (Kitchen et al., 1999). Apparent soil electrical conductivity generally accounted for yield variability better than did topographic properties (average R^2 for stepwise regression and NN was 0.21 for EC_a and 0.17 for topographic properties). Combining EC_a and topography measures together usually improved model R^2 values (average stepwise regression $R^2 = 0.32$). Apparent soil electrical conductivity provides an estimate of the within-field soil differences that have a pronounced influence on water availability (Kachanoski et al., 1990; Morgan et al., 2001). Topography effects can be similar (Timlin et al., 1998). It is not surprising that producers in rainfed crop production settings find similar patterns when comparing yield maps with EC_a maps (Lund et al., 2001). Because EC_a measurements can be used to estimate soil properties, EC_a may be used to diagnose potential rooting and water-related problems affecting grain crop production. A real value of EC_a is locating subsoil features (e.g., loam over sand at Colorado or varying topsoil thickness at Missouri) that cannot be directly observed but that can greatly impact water availability and ultimately yield.

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REFERENCES

Bell, J.C., C.A. Butler, and J.A. Thompson. 1995. Soil-terrain modeling for site-specific agricultural management. p. 210–227. *In* P.C. Robert et al. (ed.) Site-specific management for agricultural systems. Proc. Int. Conf., 2nd, Minneapolis, MN. 27–30 Mar. 1994. ASA, CSSA, and SSSA, Madison, WI.

Birrell, S.J., K.A. Sudduth, and N.R. Kitchen. 1996. Nutrient mapping implications of short-range variability. p. 207–216. *In* P.C. Robert et al. (ed.) Precision agriculture. Proc. Int. Conf., 3rd, Minneapolis, MN. 23–26 June 1996. ASA, CSSA, and SSSA, Madison, WI.

Blackmore, B.S., and C.J. Marshall. 1996. Yield mapping: Errors and algorithms. p. 403–415. *In* P.C. Robert et al. (ed.) Precision agriculture. Proc. Int. Conf., 3rd, Minneapolis, MN. 23–26 June 1996. ASA, CSSA, and SSSA, Madison, WI.

Clark, R.L., F. Chen, D.E. Kissel, and W. Adkins. 2001. Mapping soil hardpans with the penetrometer and electrical conductivity [CD-ROM]. *In* P.C. Robert et al. (ed.) Precision agriculture. Proc. Int. Conf., 5th, Minneapolis, MN. 16–19 July 2000. ASA, CSSA, and SSSA, Madison, WI.

Clark, R.L., and R. Lee. 1998. Development of topographic maps for precision farming with kinematic GPS. Trans. ASAE 41(4):909–916.

Colvin, T.S., D.B. Jaynes, D.L. Karlen, D.A. Laird, and J.R. Ambuel. 1997. Yield variability within a central Iowa field. Trans. ASAE 40(4):883–889.

Doolittle, J.A., K.A. Sudduth, N.R. Kitchen, and S.J. Indorante. 1994. Estimating depths to claypans using electromagnetic induction methods. J. Soil Water Conserv. 49:572–575.

Drummond, S.T. 1998. Application of neural techniques for spatial yield estimation. M.S. thesis. Univ. of Missouri, Columbia.

Drummond, S.T., A. Joshi, and K.A. Sudduth. 1998. Application of neural networks: Precision farming. p. 211–215. *In* Proc. Int. Joint Conf. on Neural Networks, WCCI 98, Anchorage, AK. 4–9 May 1998. IEEE Press, Piscataway, NJ.

Drummond, S.T., K.A. Sudduth, and A. Joshi. 2000. Predictive ability of neural networks for site-specific yield determination. p. 136–143. *In* Proc. Int. Conf. on Geospatial Inf. in Agric. and Forestry, 2nd, Lake Buena Vista, FL. 10–12 Jan. 2000. Vol. I. ERIM Int., Ann Arbor, MI.

Friedman, J.H., and W. Stuetzle. 1981. Projection pursuit regression. J. Am. Stat. Assoc. 76:817–823.

Geonics Limited. 1992. Geonics bibliography version 2.2. Geonics Limited, Mississauga, ON, Canada.

Geonics Limited. 1997. Applications of electromagnetic methods: Soil salinity. Geonics Limited, Mississauga, ON, Canada.

Hartsock, N.J., T.G. Mueller, G W. Thomas, R I. Barnhisel, K.L. Wells, and S.A. Shearer. 2001. Soil electrical conductivity variability [CD-ROM]. *In* P.C. Robert et al. (ed.) Precision agriculture. Proc. Int. Conf., 5th, Minneapolis, MN. 16–19 July 2000. ASA, CSSA, and SSSA, Madison, WI.

Jamison, V.C., D.D. Smith, and J.F. Thornton. 1968. Soil and water research on a claypan soil. USDA-ARS Tech. Bull. 1379. U.S. Gov. Print. Office, Washington, DC.

Jaynes, D.B. 1996. Improved soil mapping using electromagnetic induction surveys. p. 169–179. *In* P.C. Robert et al. (ed.) Precision agriculture. Proc. Int. Conf., 3rd, Minneapolis, MN. 23–26 June 1996. ASA, CSSA, and SSSA, Madison, WI.

Jaynes, D.B., T.S. Colvin, and J. Ambuel. 1993. Soil type and crop yield determinations from ground conductivity surveys. ASAE paper 933552. ASAE, St. Joseph, MI.

Jaynes, D.B., T.S. Colvin, and J. Ambuel. 1995. Yield mapping by electromagnetic induction. p. 383–394. *In* P.C. Robert et al. (ed.) Site-specific management for agricultural systems. Proc. Int. Conf.,

2nd, Minneapolis, MN. 27–30 Mar. 1994. ASA, CSSA, and SSSA, Madison, WI.
Kachanoski, R.G., E. DeJong, and I.J. Van-Wesenbeeck. 1990. Field scale patterns of soil water storage from non-contacting measurements of bulk electrical conductivity. Can. J. Soil Sci. 70:537–541.
Kitchen, N.R., K.A. Sudduth, and S.T. Drummond. 1999. Soil electrical conductivity as a crop productivity measure for claypan soils. J. Prod. Agric. 12:607–617.
Kravchenko, A.N., and D.G. Bullock. 2000. Correlation of corn and soybean grain yield with topography and soil properties. Agron. J. 92:75–83.
Lamb, J.A., J.L. Anderson, G.L. Malzer, J.A. Vetch, R.H. Dowdy, D.S. Onken, and K.I. Ault. 1995. Perils of monitoring grain yield on-the-go. *In* P.C. Robert et al. (ed.) Site-specific management for agricultural systems. Proc. Int. Conf., 2nd, Minneapolis, MN. 27–30 Mar. 1994. ASA, CSSA, and SSSA, Madison, WI.
Lark, R.M. 1997. An empirical method for describing the joint effects of environmental and other variables on crop yield. Ann. Appl. Biol. 131:141–159.
Lark, R.M., and J.V. Stafford. 1996. Consistency and change in spatial variability of crop yield over successive seasons: Methods of data analysis. p. 117–128. *In* P.C. Robert et al. (ed.) Precision agriculture. Proc. Int. Conf., 3rd, Minneapolis, MN. 23–26 June 1996. ASA, CSSA, and SSSA, Madison, WI.
Luchiari, A., J. Shanahan, D. Francis, M. Schlemmer, J. Schepers, M. Liebig, A. Schepers, and S. Payton. 2001. Strategies for establishing management zones for site specific nutrient management [CD-ROM]. *In* P.C. Robert et al. (ed.) Precision agriculture. Proc. Int. Conf., 5th, Minneapolis, MN. 16–19 July 2000. ASA, CSSA, and SSSA, Madison, WI.
Lund, E.D., C.D. Christy, and P.E. Drummond. 1999. Practical applications of soil electrical conductivity mapping. p. 771–779. *In* J.V. Stafford (ed.) Precision agriculture '99. Proc. Eur. Conf. on Precision Agric., 2nd, Odense Congress Centre, Odense, Denmark. 11–15 July 1999. SCI, Sheffield, UK.
Lund, E.D., C.D. Christy, and P.E. Drummond. 2001. Using yield and soil electrical conductivity (EC) maps to derive crop production performance information [CD-ROM]. *In* P.C. Robert et al. (ed.) Precision agriculture. Proc. Int. Conf., 5th, Minneapolis, MN. 16–19 July 2000. ASA, CSSA, and SSSA, Madison, WI.
McNeil, J.D. 1992. Rapid, accurate mapping of soil salinity by electromagnetic ground conductivity meters. p. 201–229. *In* Advances in measurements of soil physical properties: Bringing theory into practice. SSSA Spec. Publ. 30. SSSA, Madison, WI.
Morgan, C.L.S., J.M. Norman, R.P. Wolkowski, B. Lowery, G.D. Morgan, and R. Schuler. 2001. Two approaches to mapping plant available water: EM-38 measurements and inverse yield modeling [CD-ROM]. *In* P.C. Robert et al. (ed.) Precision agriculture. Proc. Int. Conf., 5th, Minneapolis, MN. 16–19 July 2000. ASA, CSSA, and SSSA, Madison, WI.
Nolin, M.C., G. Forand, R.R. Simard, A.N. Cambouris, and A. Karam. 2001. Soil specific relationships between corn/soybean yield, soil quality indicators and climatic data [CD-ROM]. *In* P.C. Robert et al. (ed.) Precision agriculture. Proc. Int. Conf., 5th, Minneapolis, MN. 16–19 July 2000. ASA, CSSA, and SSSA, Madison, WI.
Pierce, F.J., N.W. Anderson, T.S. Colvin, J.K. Schueller, D.S. Humburg, and N.B. McLauglhlin. 1997. Yield mapping. p. 211–243. *In* F.J. Pierce and E.J. Sadler (ed.) The state of site-specific management for agriculture. ASA, CSSA, and SSSA, Madison, WI.
Pierce, F.J., and P. Nowak. 1999. Aspects of precision agriculture. Adv. Agron. 67:1–85.
Reidmiller, M., and H. Braun. 1993. A direct adaptive method for faster backpropagation learning: The RPROP algorithm. p. 586–591. *In* H. Ruspini (ed.) Proc IEEE Int. Conf. on Neural Networks (ICNN), San Francisco. 28 Mar.–1 Apr. 1993. IEEE Neural Networks Counc., IEEE, Piscataway, NJ.
Rumelhart, D.E., and J.L. McClelland. 1986. Parallel distributed processing: Volume 1. MIT Press, Cambridge, MA.
Sawyer, J.E. 1994. Concepts of variable rate technology with considerations for fertilizer application. J. Prod. Agric. 7:195–201.
Sudduth, K.A., S.T. Drummond, S.J. Birrell, and N.R. Kitchen. 1996. Analysis of spatial factors influencing crop yield. p. 129–140. *In* P.C. Robert et al. (ed.) Precision agriculture. Proc. Int. Conf., 3rd, Minneapolis, MN. 23–26 June 1996. ASA, CSSA, and SSSA, Madison, WI.
Sudduth, K.A., S.T. Drummond, S.J. Birrell, and N.R. Kitchen. 1997. Spatial modeling of crop yield using soil and topographic data. p. 439–447. *In* J.V. Stafford (ed.) Precision agriculture '97. Proc. Eur. Conf. on Precision Agric., 1st, Warwick Univ. Conf. Cent., Coventry, UK. 7–10 Sept. 1997. Vol. 1. SCI, London.
Sudduth, K.A., S.T. Drummond, and N.R. Kitchen. 2001. Accuracy issues in electromagnetic induction sensing of soil electrical conductivity for precision agriculture. Comput. Electron. Agric. 31:239–264.
Sudduth, K.A., N.R. Kitchen, G.A. Bollero, D.G. Bullock, and W.J. Wiebold. 2003. Comparison of electromagnetic induction and direct sensing of soil electrical conductivity. Agron. J. 95:472–482 (this issue).
Sudduth, K.A., N.R. Kitchen, and S.T. Drummond. 1999. Soil conductivity sensing on claypan soils: Comparison of electromagnetic induction and direct methods. p. 979–990. *In* Precision agriculture. Proc. Int. Conf., 4th, St. Paul, MN. 19–22 July 1998. Vol. II. ASA, CSSA, and SSSA, Madison, WI.
Sudduth, K.A., N.R. Kitchen, D.F. Hughes, and S.T. Drummond. 1995. Electromagnetic induction sensing as an indicator of productivity on claypan soils. p. 671–681. *In* P.C. Robert et al. (ed.) Site-specific management for agricultural systems. Proc. Int. Conf., 2nd, Minneapolis, MN. 27–30 Mar. 1994. ASA, CSSA, and SSSA, Madison, WI.
Thompson, A.L., C.J. Gantzer, and S.H. Anderson. 1991. Topsoil depth, fertility, water management, and weather influences on yield. Soil Sci. Soc. Am. J. 55:1085–1091.
Timlin, D.J., Y.A. Pachepsky, V.A. Snyder, and R.B. Bryant. 1998. Spatial and temporal variability of corn grain yield on a hillslope. Soil Sci. Soc. Am. J. 62:764–773.
U.S. Department of Agriculture Natural Resources Conservation Service. 1995. Soil survey of Audrain County, Missouri (1995–387–974/00537/SCS). U.S. Gov. Print. Office, Washington, DC.
Ward, B.D., and M.S. Cox. 2001. Influences of soil chemical and physical properties on site-specific cotton production [CD-ROM]. *In* P.C. Robert et al. (ed.) Precision agriculture. Proc. Int. Conf., 5th, Minneapolis, MN. 16–19 July 2000. ASA, CSSA, and SSSA, Madison, WI.
Webb, R.A. 1972. Use of boundary line in the analysis of biological data. J. Hortic. Sci. 47:309–319.
Weibel, R., and M. Heller. 1991. Digital terrain modelling. p. 269–297. *In* M.F. Goodchild and D. Rhines (ed.) Geographic information systems: Principles and applications. Taylor and Francis, New York.
Wiebold, W.J., K.A. Sudduth, J.G. Davis, D.K. Shannon, and N.R. Kitchen. 1998. Determining barriers to adoption and research needs of precision agriculture [Online]. Available at http://www.fse.missouri.edu/mpac/pubs/parpt.pdf (verified 3 Feb. 2003). Food Sci. and Biol. Eng. Unit, Univ. of Missouri, Columbia.
Zhang, N., and R. Taylor. 2001. Applications of a field-level geographic information system (FIS) in precision agriculture [CD-ROM]. *In* P.C. Robert et al. (ed.) Precision agriculture. Proc. Int. Conf., 5th, Minneapolis, MN. 16–19 July 2000. ASA, CSSA, and SSSA, Madison, WI.